Monocular Visual-Inertial SLAM for ISMAR SLAM Challenge

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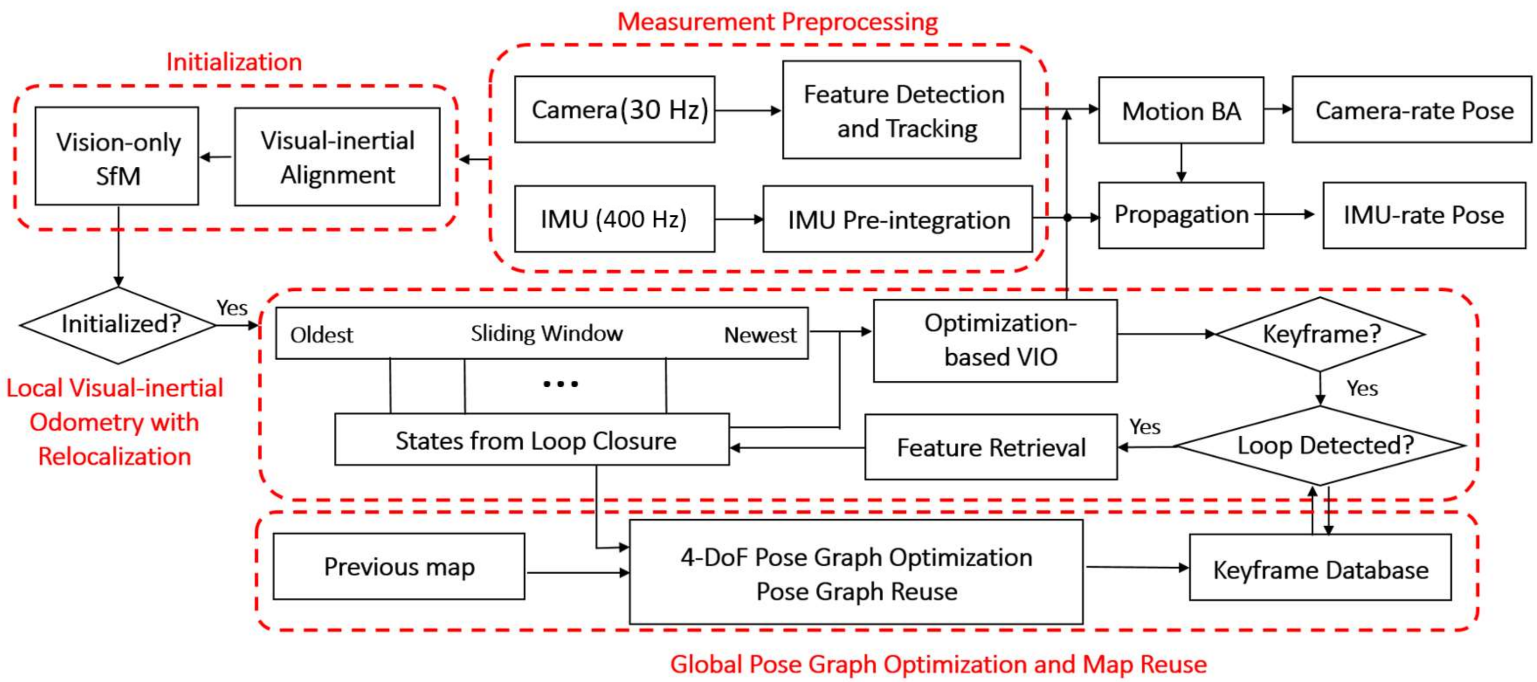
Source Code: http://github.com/HKUST-Aerial-Robotics/VINS-Mono

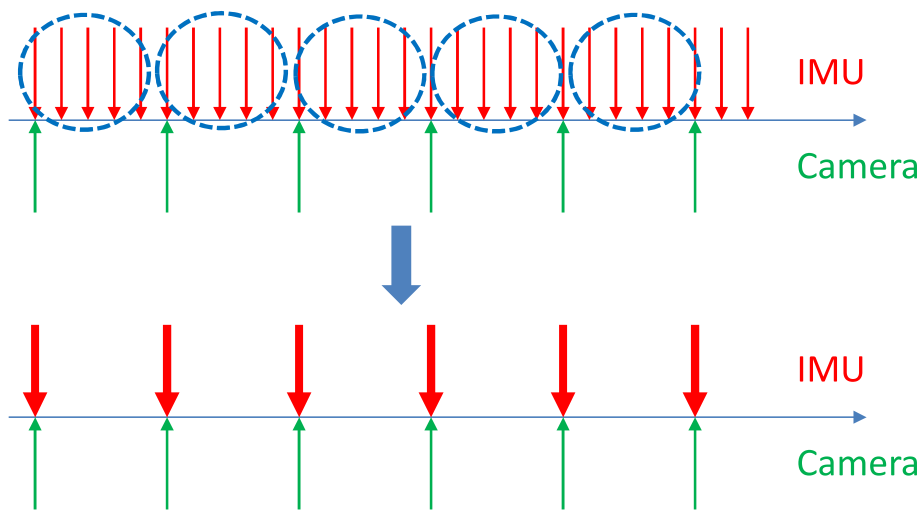
Monocular Visual-Inertial SLAM

- System diagram



How to Use IMU?

- IMU integration
  - IMU has higher rate than camera
  - Cannot estimate all IMU states
  - Need to integration IMU measurements



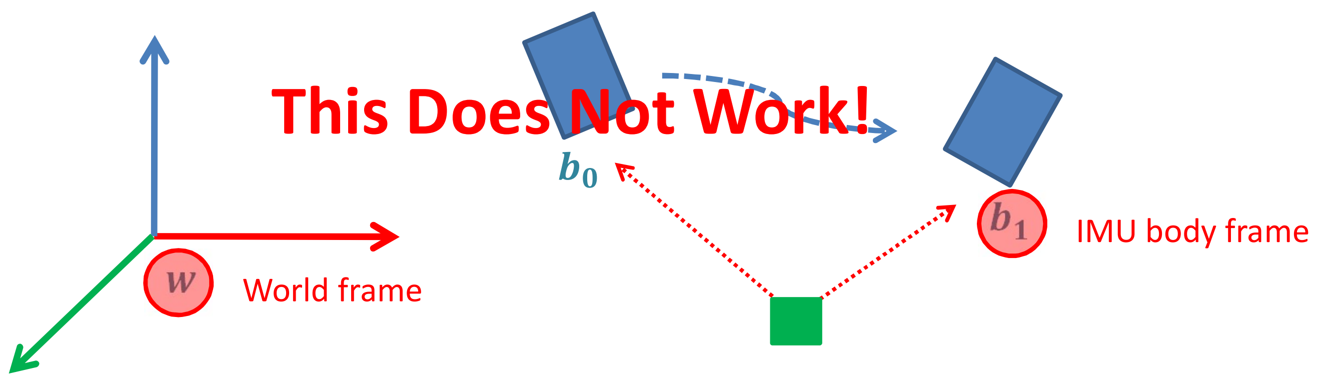
The Bad of IMU Integration in the Global Frame

- IMU integration in world frame
  - Requires global rotation at the time of integration

$$\mathbf{p}^w_{b_{k+1}} = \mathbf{p}^w_{b_k} + \mathbf{v}^w_{b_k}\Delta t_k + \iint_{t\in[t_k,t_{k+1}]} \left(\mathbf{R}^w_t(\hat{\mathbf{a}}_t - \mathbf{b}_{a_t} - \mathbf{n}_a) - \mathbf{g}^w\right) dt^2$$

$$\mathbf{v}^w_{b_{k+1}} = \mathbf{v}^w_{b_k} + \int_{t\in[t_k,t_{k+1}]} \left(\mathbf{R}^w_t(\hat{\mathbf{a}}_t - \mathbf{b}_{a_t} - \mathbf{n}_a) - \mathbf{g}^w\right) dt$$

$$\mathbf{q}^w_{b_{k+1}} = \mathbf{q}^w_{b_k} \otimes \int_{t\in[t_k,t_{k+1}]} \frac{1}{2}\boldsymbol{\Omega}(\hat{\boldsymbol{\omega}}_t - \mathbf{b}_{w_t} - \mathbf{n}_w)\mathbf{q}^{b_k}_t dt, \quad \boldsymbol{\Omega}(\boldsymbol{\omega}) = \begin{bmatrix} -\lfloor\boldsymbol{\omega}\rfloor_\times & \boldsymbol{\omega} \\ -\boldsymbol{\omega}^T & 0 \end{bmatrix}, \lfloor\boldsymbol{\omega}\rfloor_\times = \begin{bmatrix} 0 & -\omega_z & \omega_y \\ \omega_z & 0 & -\omega_x \\ -\omega_y & \omega_x & 0 \end{bmatrix}.$$

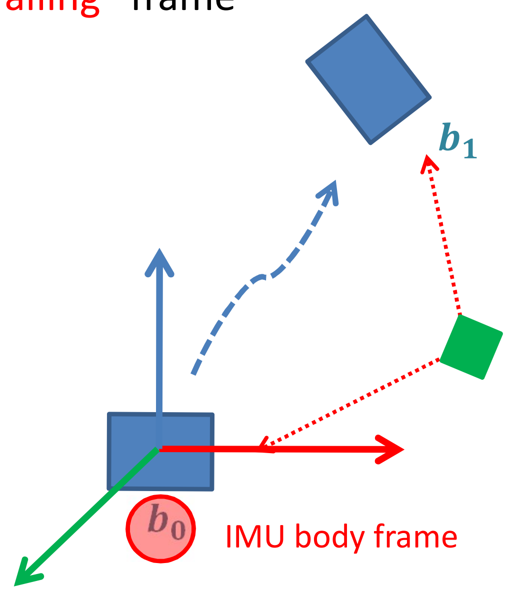


IMU Pre-Integration on Manifold

- IMU integration in the body frame of first pose of interests
  - IMU Integration without initialization
  - Can use any discrete implementation for numerical integration
  - Intuitive: "position" and "velocity" changes in a "free-falling" frame

$$\begin{aligned}
\mathbf{R}_w^{b_k}\mathbf{p}_{b_{k+1}}^w &= \mathbf{R}_w^{b_k}(\mathbf{p}_{b_k}^w + \mathbf{v}_{b_k}^w \Delta t_k - \frac{1}{2}\mathbf{g}^w \Delta t_k^2) + \boldsymbol{\alpha}_{b_{k+1}}^{b_k} \\
\mathbf{R}_w^{b_k}\mathbf{v}_{b_{k+1}}^w &= \mathbf{R}_w^{b_k}(\mathbf{v}_{b_k}^w - \mathbf{g}^w \Delta t_k) + \boldsymbol{\beta}_{b_{k+1}}^{b_k} \\
\mathbf{q}_w^{b_k} \otimes \mathbf{q}_{b_{k+1}}^w &= \boldsymbol{\gamma}_{b_{k+1}}^{b_k},
\end{aligned}$$

$$\begin{aligned}
\boldsymbol{\alpha}_{b_{k+1}}^{b_k} &= \iint_{t\in[t_k,t_{k+1}]} \mathbf{R}_t^{b_k}(\hat{\mathbf{a}}_t - \mathbf{b}_{a_t} - \mathbf{n}_a)dt^2 \\
\boldsymbol{\beta}_{b_{k+1}}^{b_k} &= \int_{t\in[t_k,t_{k+1}]} \mathbf{R}_t^{b_k}(\hat{\mathbf{a}}_t - \mathbf{b}_{a_t} - \mathbf{n}_a)dt \\
\boldsymbol{\gamma}_{b_{k+1}}^{b_k} &= \int_{t\in[t_k,t_{k+1}]} \frac{1}{2}\boldsymbol{\Omega}(\hat{\boldsymbol{\omega}}_t - \mathbf{b}_{w_t} - \mathbf{n}_w)\boldsymbol{\gamma}_t^{b_k} dt.
\end{aligned}$$



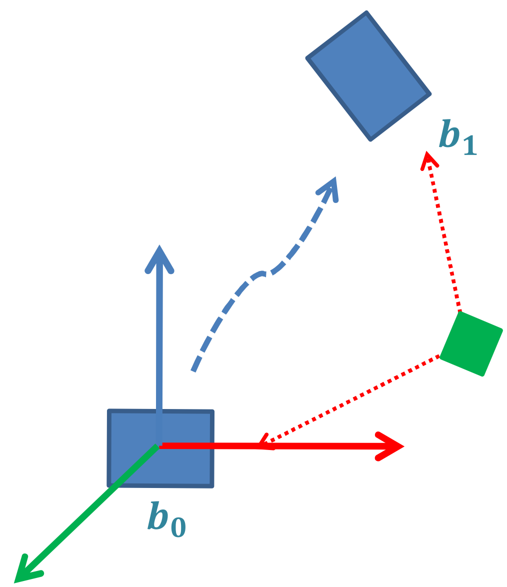
IMU Pre-Integration on Manifold

- Uncertainty propagation on manifold
  - Derive the error state model for the IMU pre-integration dynamics

$$
\begin{bmatrix} \delta\dot{\boldsymbol{\alpha}}_t^{b_k} \\ \delta\dot{\boldsymbol{\beta}}_t^{b_k} \\ \delta\dot{\boldsymbol{\theta}}_t^{b_k} \\ \delta\dot{\mathbf{b}}_{a_t} \\ \delta\dot{\mathbf{b}}_{w_t} \end{bmatrix} = \begin{bmatrix} 0 & \mathbf{I} & 0 & 0 & 0 \\ 0 & 0 & -\mathbf{R}_t^{b_k}\lfloor \hat{\mathbf{a}}_t - \mathbf{b}_{a_t} \rfloor_\times & -\mathbf{R}_t^{b_k} & 0 \\ 0 & 0 & -\lfloor \hat{\boldsymbol{\omega}}_t - \mathbf{b}_{w_t} \rfloor_\times & 0 & -\mathbf{I} \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} \delta\boldsymbol{\alpha}_t^{b_k} \\ \delta\boldsymbol{\beta}_t^{b_k} \\ \delta\boldsymbol{\theta}_t^{b_k} \\ \delta\mathbf{b}_{a_t} \\ \delta\mathbf{b}_{w_t} \end{bmatrix}
$$

Bias uncertainty

$$
+ \begin{bmatrix} 0 & 0 & 0 & 0 \\ -\mathbf{R}_t^{b_k} & 0 & 0 & 0 \\ 0 & -\mathbf{I} & 0 & 0 \\ 0 & 0 & \mathbf{I} & 0 \\ 0 & 0 & 0 & \mathbf{I} \end{bmatrix} \begin{bmatrix} \mathbf{n}_a \\ \mathbf{n}_w \\ \mathbf{n}_{b_a} \\ \mathbf{n}_{b_w} \end{bmatrix} = \mathbf{F}_t \delta\mathbf{z}_t^{b_k} + \mathbf{G}_t \mathbf{n}_t .
$$



  - Discrete-time implementation

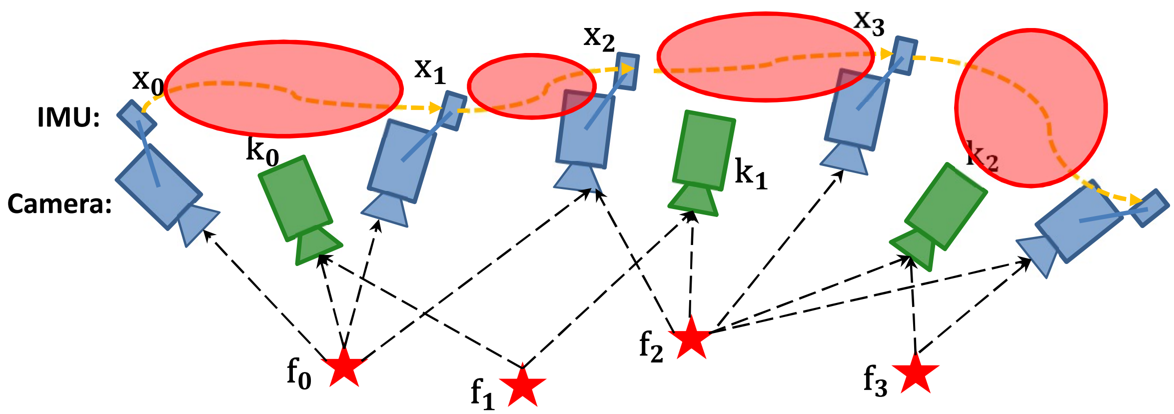
$$
\mathbf{P}_{t+\delta t}^{b_k} = (\mathbf{I} + \mathbf{F}_t \delta t)\mathbf{P}_t^{b_k}(\mathbf{I} + \mathbf{F}_t \delta t)^T + \delta t \mathbf{G}_t \mathbf{Q}_t \mathbf{G}_t{}^T, \quad t \in [k, k+1].
$$

Covariance matrix for pre-integrated IMU measurements

IMU Pre-Integration on Manifold

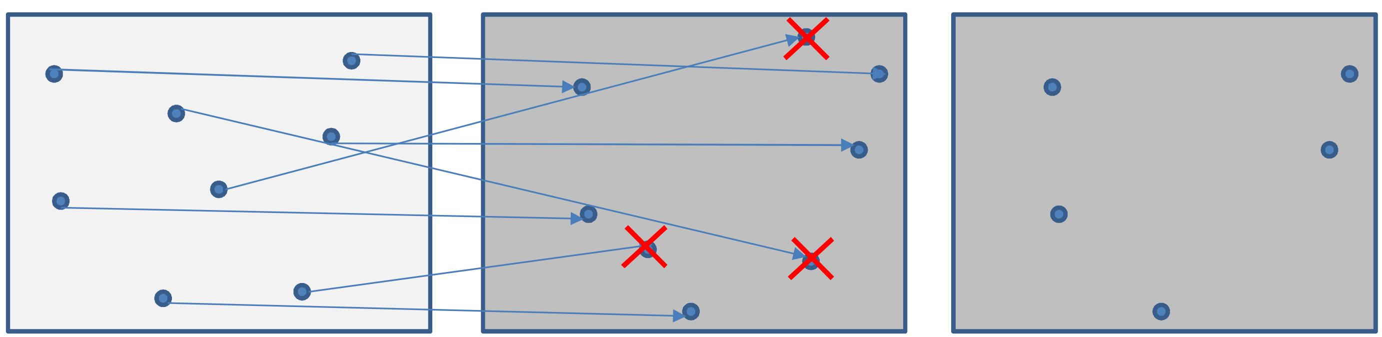
- Pre-integrated IMU measurement model
  - Describes the spatial and uncertainty relations between two states in the local sliding window

$$\begin{bmatrix} \hat{\alpha}^{b_k}_{b_{k+1}} \\ \hat{\beta}^{b_k}_{b_{k+1}} \\ \hat{\gamma}^{b_k}_{b_{k+1}} \\ \mathbf{0} \\ \mathbf{0} \end{bmatrix} = \begin{bmatrix} \mathbf{R}^{b_k}_w(\mathbf{p}^w_{b_{k+1}} - \mathbf{p}^w_{b_k} + \frac{1}{2}\mathbf{g}^w \Delta t_k^2 - \mathbf{v}^w_{b_k}\Delta t_k) \\ \mathbf{R}^{b_k}_w(\mathbf{v}^w_{b_{k+1}} + \mathbf{g}^w \Delta t_k - \mathbf{v}^w_{b_k}) \\ \mathbf{q}^{w^{-1}}_{b_k} \otimes \mathbf{q}^w_{b_{k+1}} \\ \mathbf{b}_{ab_{k+1}} - \mathbf{b}_{ab_k} \\ \mathbf{b}_{wb_{k+1}} - \mathbf{b}_{wb_k} \end{bmatrix}$$



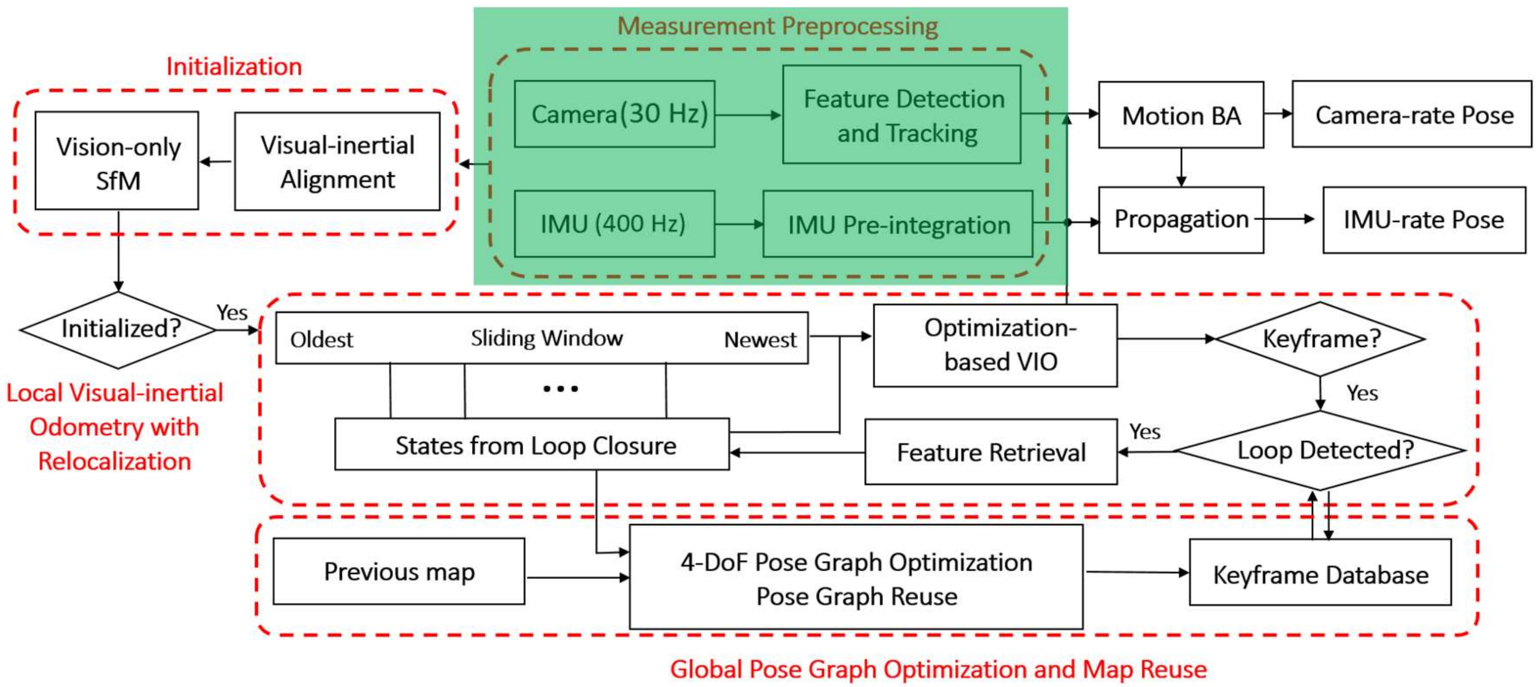
Vision Front-End

- Simple feature processing pipeline
  - Harris corners…
  - KLT tracker...
  - Track between consecutive frames, flow back
  - RANSAC for preliminary outlier removal



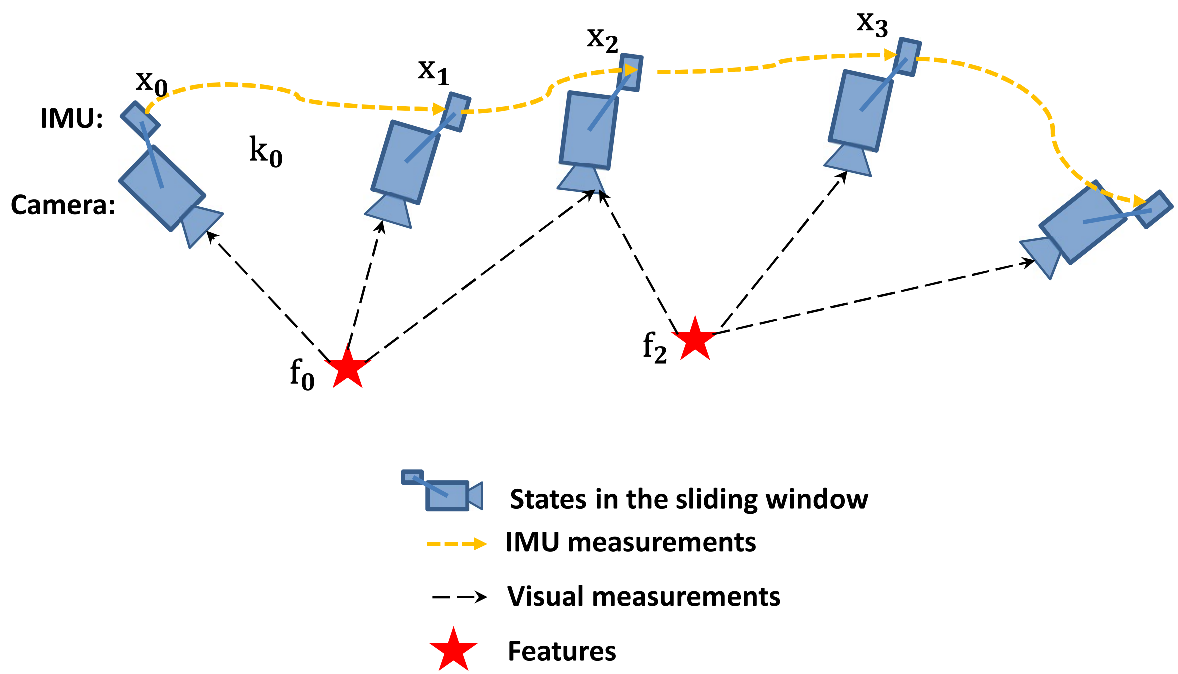
Monocular Visual-Inertial SLAM

- System diagram



Monocular Visual-Inertial Odometry

- Nonlinear graph optimization-based, tightly-coupled, sliding window, visual-inertial bundle adjustment



Monocular Visual-Inertial Odometry

- Nonlinear graph-based optimization
  - Optimize position, velocity, rotation, IMU biases, inverse feature depth, and camera-IMU extrinsic calibration simultaneously:

$$
\begin{aligned}
\mathcal{X} &= \left[\mathbf{x}_0,\, \mathbf{x}_1,\, \cdots \mathbf{x}_n,\, \mathbf{x}_c^b,\, \lambda_0,\, \lambda_1,\, \cdots \lambda_m\right] \\
\mathbf{x}_k &= \left[\mathbf{p}_{b_k}^w,\, \mathbf{v}_{b_k}^w,\, \mathbf{q}_{b_k}^w,\, \mathbf{b}_a,\, \mathbf{b}_g\right], k \in [0, n] \\
\mathbf{x}_c^b &= \left[\mathbf{p}_c^b,\, \mathbf{q}_c^b\right],
\end{aligned}
$$

  - Minimize residuals from all sensors

IMU measurement residual

Vision measurement residual

$$
\min_{\mathcal{X}} \left\{ \left\| \mathbf{r}_p - \mathbf{H}_p \mathcal{X} \right\|^2 + \sum_{k \in \mathcal{B}} \left\| \mathbf{r}_{\mathcal{B}}(\hat{\mathbf{z}}_{b_{k+1}}^{b_k}, \mathcal{X}) \right\|_{\mathbf{P}_{b_{k+1}}^{b_k}}^2 + \sum_{(l,j) \in \mathcal{C}} \left\| \mathbf{r}_{\mathcal{C}}(\hat{\mathbf{z}}_l^{c_j}, \mathcal{X}) \right\|_{\mathbf{P}_l^{c_j}}^2 \right\}
$$

Prior from marginalization

Covariance from IMU pre-integration

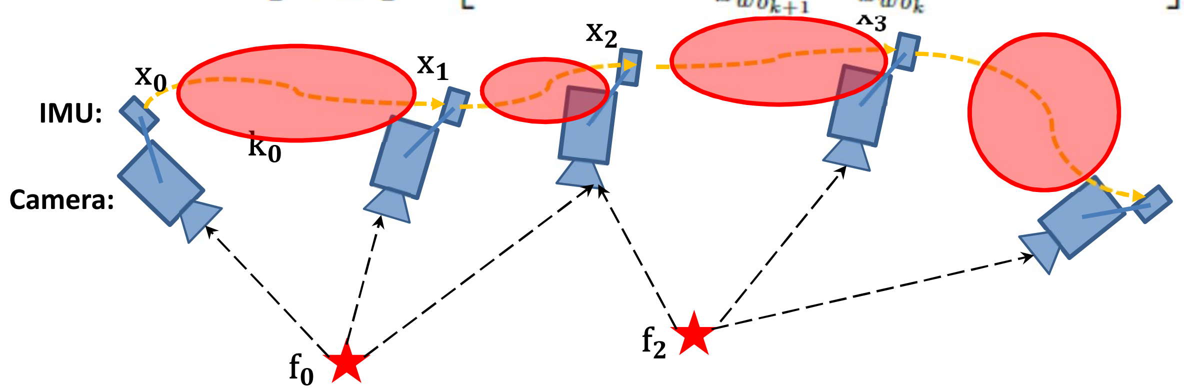
Pixel reprojection covariance

Monocular Visual-Inertial Odometry

- IMU measurement residual
  - Additive for "position" and "velocity" changes, and biases
  - Multiplicative for incremental rotation

IMU pre-integration "blocks"

$$\mathbf{r}_{\mathcal{B}}(\hat{\mathbf{z}}^{b_k}_{b_{k+1}}, \mathcal{X}) = \begin{bmatrix} \delta\boldsymbol{\alpha}^{b_k}_{b_{k+1}} \\ \delta\boldsymbol{\beta}^{b_k}_{b_{k+1}} \\ \delta\boldsymbol{\theta}^{b_k}_{b_{k+1}} \\ \delta\mathbf{b}_a \\ \delta\mathbf{b}_g \end{bmatrix} = \begin{bmatrix} \mathbf{R}^{b_k}_w(\mathbf{p}^w_{b_{k+1}} - \mathbf{p}^w_{b_k} + \frac{1}{2}\mathbf{g}^w\Delta t_k^2 - \mathbf{v}^w_{b_k}\Delta t_k) - \hat{\boldsymbol{\alpha}}^{b_k}_{b_{k+1}} \\ \mathbf{R}^{b_k}_w(\mathbf{v}^w_{b_{k+1}} + \mathbf{g}^w\Delta t_k - \mathbf{v}^w_{b_k}) - \hat{\boldsymbol{\beta}}^{b_k}_{b_{k+1}} \\ 2\left[\mathbf{q}^{w^{-1}}_{b_{k+1}} \otimes \mathbf{q}^w_{b_k} \otimes \hat{\boldsymbol{\gamma}}^{b_k}_{b_{k+1}}\right]_{xyz} \\ \mathbf{b}_{ab_{k+1}} - \mathbf{b}_{ab_k} \\ \mathbf{b}_{wb_{k+1}} - \mathbf{b}_{wb_k} \end{bmatrix}$$



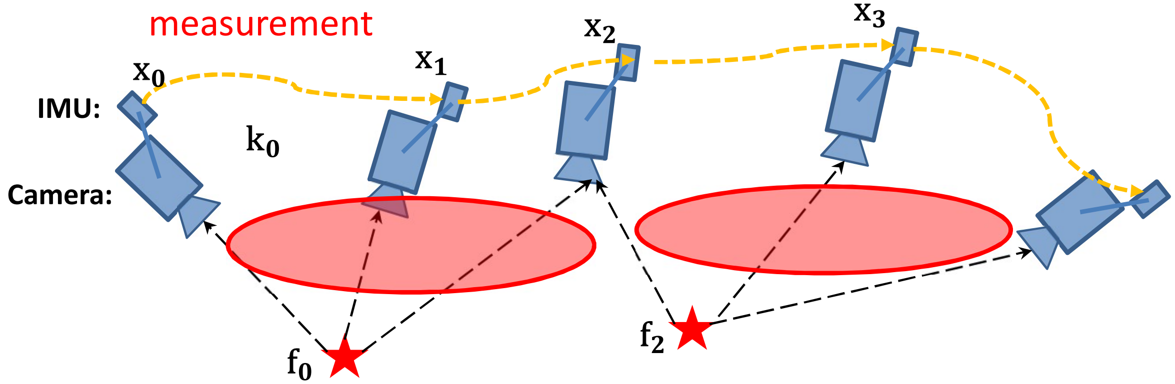
Monocular Visual-Inertial Odometry

- Vision measurement residual
  - Pixel reprojection error
  - Inverse depth model, at least 2 observations per feature, first observation to define feature direction

$$\mathbf{r}_{\mathcal{C}}(\hat{\mathbf{z}}_l^{c_j}, \mathcal{X}) = \begin{bmatrix} \hat{u}_l^{c_j} \\ \hat{v}_l^{c_j} \end{bmatrix} - \pi_c(\mathbf{R}_b^c(\mathbf{R}_w^{b_j}(\mathbf{R}_{b_i}^w(\mathbf{R}_c^b \frac{1}{\lambda_l} \pi_c^{-1}(\begin{bmatrix} u_l^{c_i} \\ v_l^{c_i} \end{bmatrix}) + \mathbf{p}_c^b) + \mathbf{p}_{b_i}^w - \mathbf{p}_{b_j}^w) - \mathbf{p}_c^b))$$

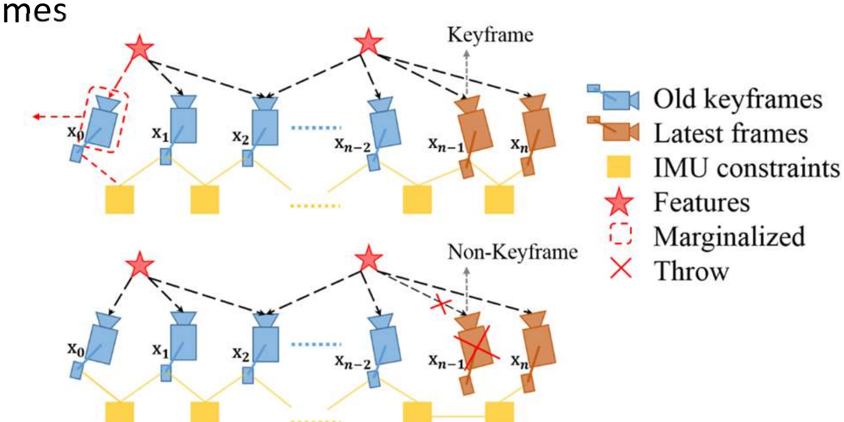
Actual feature measurement

Predicted pixel location in camera frame



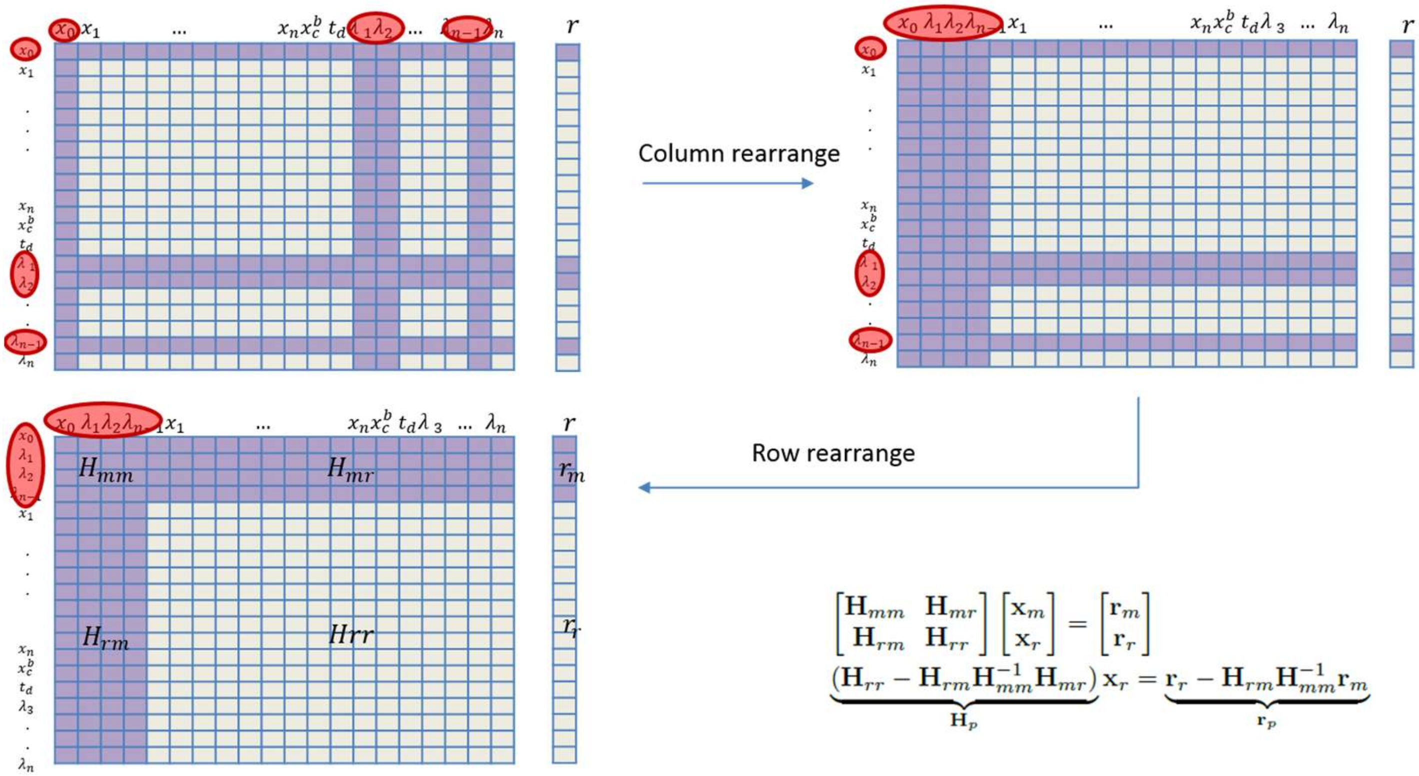
Monocular Visual-Inertial Odometry

- Marginalization
  - Bound computation complexity to a sliding window of states
  - Basic principles:
    - Add all frames into the sliding window, and remove non-keyframes after the nonlinear optimization
    - keep as many keyframes with sufficient parallax as possible
    - Maintain matrix sparsity by throwing away visual measurements from non-keyframes



Monocular Visual-Inertial Odometry

- Marginalization via Schur complement on information matrix



$$\begin{bmatrix}\mathbf{H}_{mm} & \mathbf{H}_{mr}\\ \mathbf{H}_{rm} & \mathbf{H}_{rr}\end{bmatrix}\begin{bmatrix}\mathbf{x}_m\\ \mathbf{x}_r\end{bmatrix}=\begin{bmatrix}\mathbf{r}_m\\ \mathbf{r}_r\end{bmatrix}$$

$$\underbrace{(\mathbf{H}_{rr}-\mathbf{H}_{rm}\mathbf{H}_{mm}^{-1}\mathbf{H}_{mr})}_{\mathbf{H}_p}\mathbf{x}_r=\underbrace{\mathbf{r}_r-\mathbf{H}_{rm}\mathbf{H}_{mm}^{-1}\mathbf{r}_m}_{\mathbf{r}_p}$$

Monocular Visual-Inertial Odometry

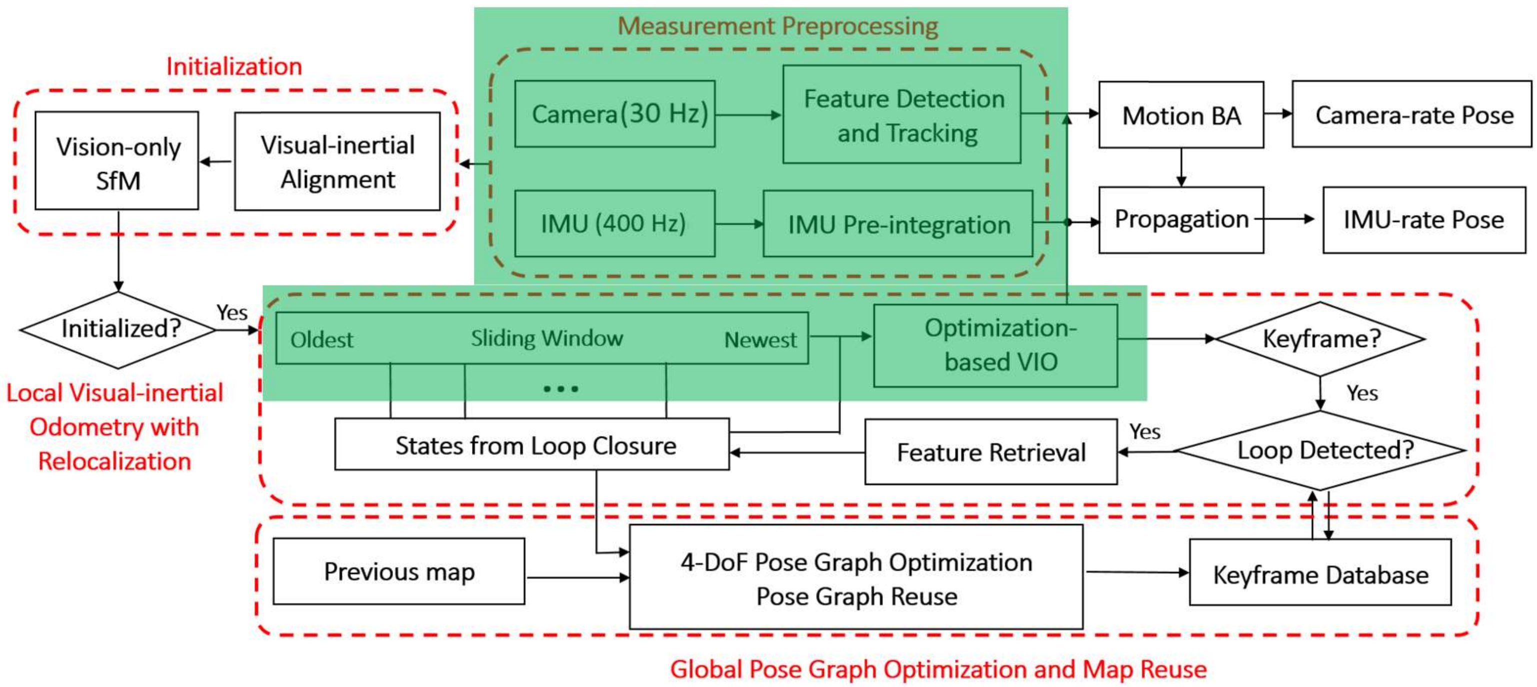
- Solving the nonlinear system
  - Minimize residuals from all sensors

$$\min_{\mathcal{X}} \left\{ \left\| \mathbf{r}_p - \mathbf{H}_p \mathcal{X} \right\|^2 + \sum_{k \in \mathcal{B}} \left\| \mathbf{r}_{\mathcal{B}} (\hat{\mathbf{z}}_{b_{k+1}}^{b_k}, \mathcal{X}) \right\|_{\mathbf{P}_{b_{k+1}}^{b_k}}^2 + \sum_{(l,j) \in \mathcal{C}} \left\| \mathbf{r}_{\mathcal{C}} (\hat{\mathbf{z}}_l^{c_j}, \mathcal{X}) \right\|_{\mathbf{P}_l^{c_j}}^2 \right\}$$

  - Linearize (to Ax=b), solve, and iterate until time budget is reached
  - Ceres Solver (http://ceres-solver.org/)

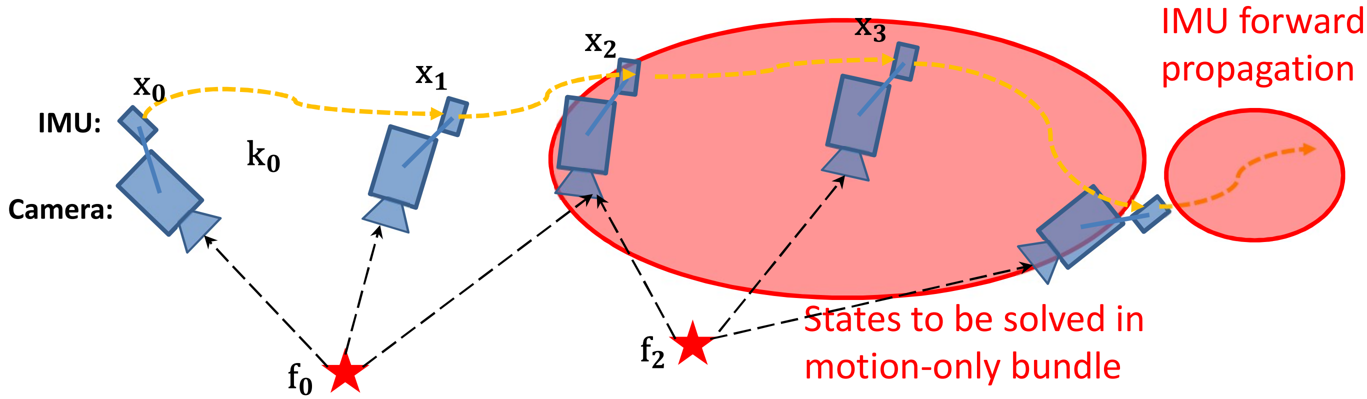
Monocular Visual-Inertial SLAM

- System diagram



Monocular Visual-Inertial Odometry

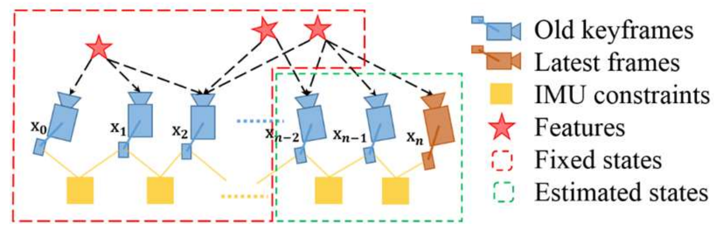
- Speeding up
  - The sliding window monocular visual-inertial bundle adjustment runs at 10Hz
  - Motion-only visual-inertial bundle adjustment to boost up the state estimation 30Hz
  - IMU forward propagation to boost to 400Hz



Monocular Visual-Inertial Odometry

- Motion-only visual-inertial bundle adjustment
  - Optimize position, velocity, rotation in a smaller windows, assuming all other quantities are fixed

$$\mathcal{X} = [\cancel{\mathbf{x}_0, \mathbf{x}_1, \cdots} \mathbf{x}_n, \cancel{\mathbf{x}_c^b, \lambda_0, \lambda_1, \cdots \lambda_m}]$$
$$\mathbf{x}_k = [\mathbf{p}^w_{b_k}, \mathbf{v}^w_{b_k}, \mathbf{q}^w_{b_k}, \cancel{\mathbf{b}_a, \mathbf{b}_g}], k \in [0, n]$$
$$\cancel{\mathbf{x}_c^b = [\mathbf{p}_c^b, \mathbf{q}_c^b]},$$



  - Prior in cost function is ignored

IMU measurement residual   Vision measurement residual

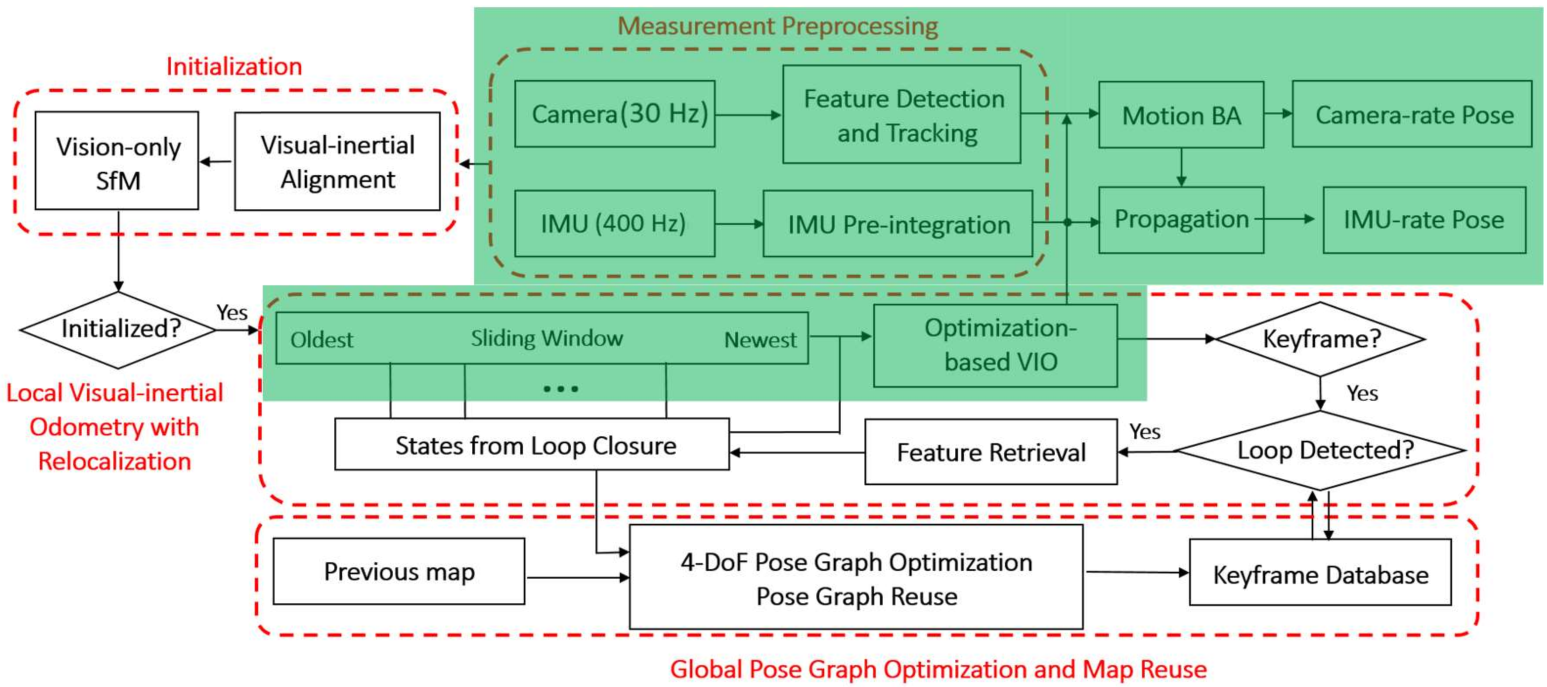
$$\min_{\mathcal{X}} \left\{ \cancel{\|\mathbf{r}_p - \mathbf{H}_p \mathcal{X}\|^2} + \sum_{k \in \mathcal{B}} \left\| \mathbf{r}_{\mathcal{B}}(\hat{\mathbf{z}}^{b_k}_{b_{k+1}}, \mathcal{X}) \right\|^2_{\mathbf{P}^{b_k}_{b_{k+1}}} + \sum_{(l,j) \in \mathcal{C}} \left\| \mathbf{r}_{\mathcal{C}}(\hat{\mathbf{z}}^{c_j}_l, \mathcal{X}) \right\|^2_{\mathbf{P}^{c_j}_l} \right\}$$

Covariance from IMU pre-integration   Pixel reprojection covariance

  - Also solved using the Ceres Solver

Monocular Visual-Inertial SLAM

- System diagram

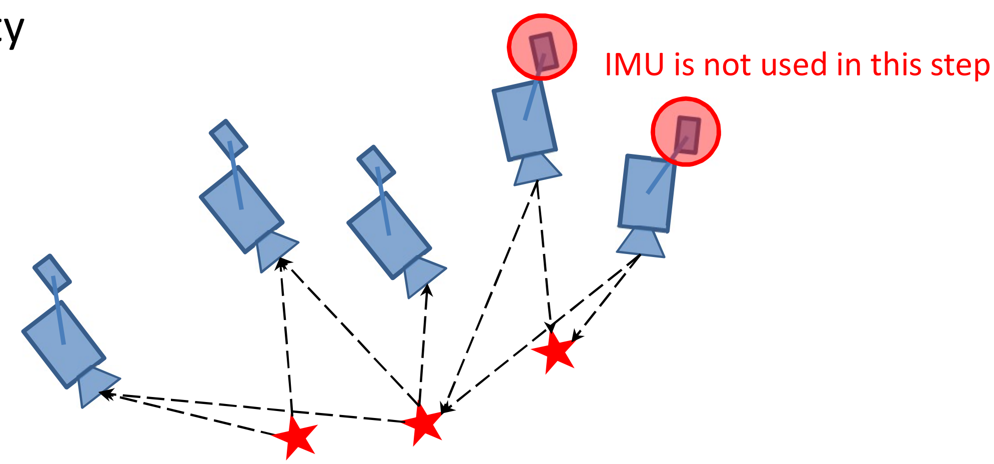


Estimator Initialization

- Very, very, very important for monocular visual-inertial systems
- Assumption 1: known camera-IMU extrinsic calibration during initialization
  - Does not need to be very accurate
  - Extrinsic calibration is refined in later nonlinear optimization
- Assumption 2: known accelerometer and gyroscope biases during initialization
  - Use zero values at power-up
  - Use prior values during failure recovery
  - Reasonable assumption due to slow varying nature of biases
- Pipeline
  - Monocular vision-only SFM in a local window
  - Visual-inertial alignment

Estimator Initialization

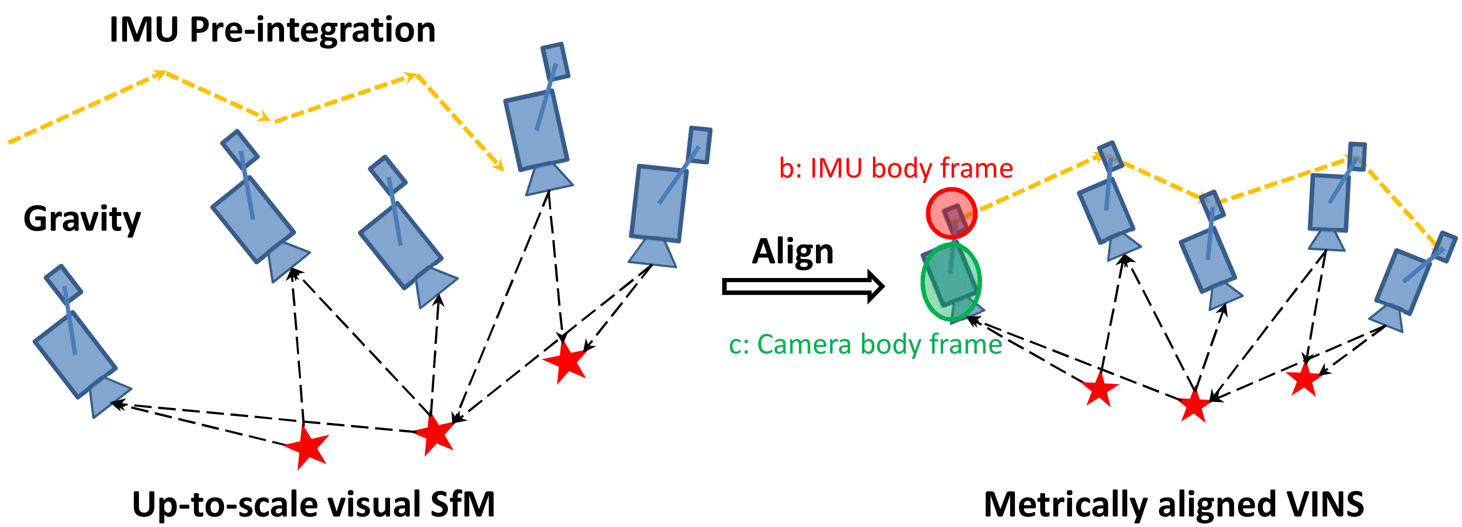
- Monocular vision-only structure-from-motion (SfM)
  - In a small window (10 frames, 1sec)
  - Up-to-scale, locally drift-free position estimates
  - Locally drift-free orientation estimates
  - Not aligned with gravity



Estimator Initialization

- Visual-inertial alignment
  - Estimates velocity of each frame, gravity vector, and scale
    - Note the coordinate frames

$$\mathcal{X}_I = \left[\mathbf{v}_{b_0}^{c_0}, \mathbf{v}_{b_1}^{c_0}, \cdots \mathbf{v}_{b_n}^{c_0}, \mathbf{g}^{c_0}, s\right]$$



Estimator Initialization

- Visual-inertial alignment
  - Linear measurement model

IMU Pre-integration

Known values from vSfM and extrinsic calibration

$$\hat{\mathbf{z}}^{b_k}_{b_{k+1}} = \begin{bmatrix} \hat{\alpha}^{b_k}_{b_{k+1}} - \mathbf{R}^{c_0}_{c_{k+1}}\mathbf{p}^c_b + \mathbf{R}^{c_0}_{c_k}\mathbf{p}^c_b \\ \hat{\beta}^{b_k}_{b_{k+1}} \end{bmatrix} = \mathbf{H}^{b_k}_{b_{k+1}}\mathcal{X}_I + \mathbf{n}^{b_k}_{b_{k+1}}$$

$$\approx \begin{bmatrix} -\mathbf{R}^{b_k}_{c_0}\Delta t_k & \mathbf{0} & \frac{1}{2}\mathbf{R}^{b_k}_{c_0}\Delta t_k^2 & \mathbf{R}^{b_k}_{c_0}(\bar{\mathbf{p}}^{c_0}_{c_{k+1}} - \bar{\mathbf{p}}^{c_0}_{c_k}) \\ -\mathbf{R}^{b_k}_{c_0} & \mathbf{R}^{b_k}_{c_0} & \mathbf{R}^{b_k}_{c_0}\Delta t_k & \mathbf{0} \end{bmatrix} \begin{bmatrix} \mathbf{v}^{c_0}_{b_k} \\ \mathbf{v}^{c_0}_{b_{k+1}} \\ \mathbf{g}^{c_0} \\ s \end{bmatrix}$$

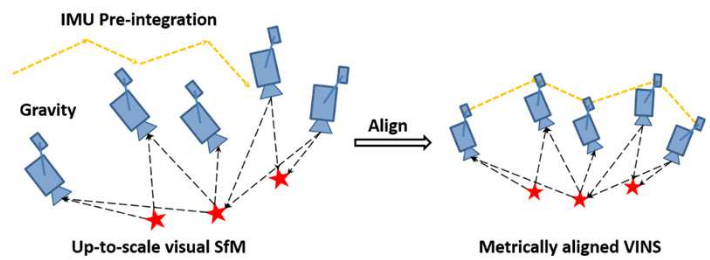
States to be initialized

Up-to-scale translation from vSfM

  - Solve a linear system
    - Scale and rotate the vSfM

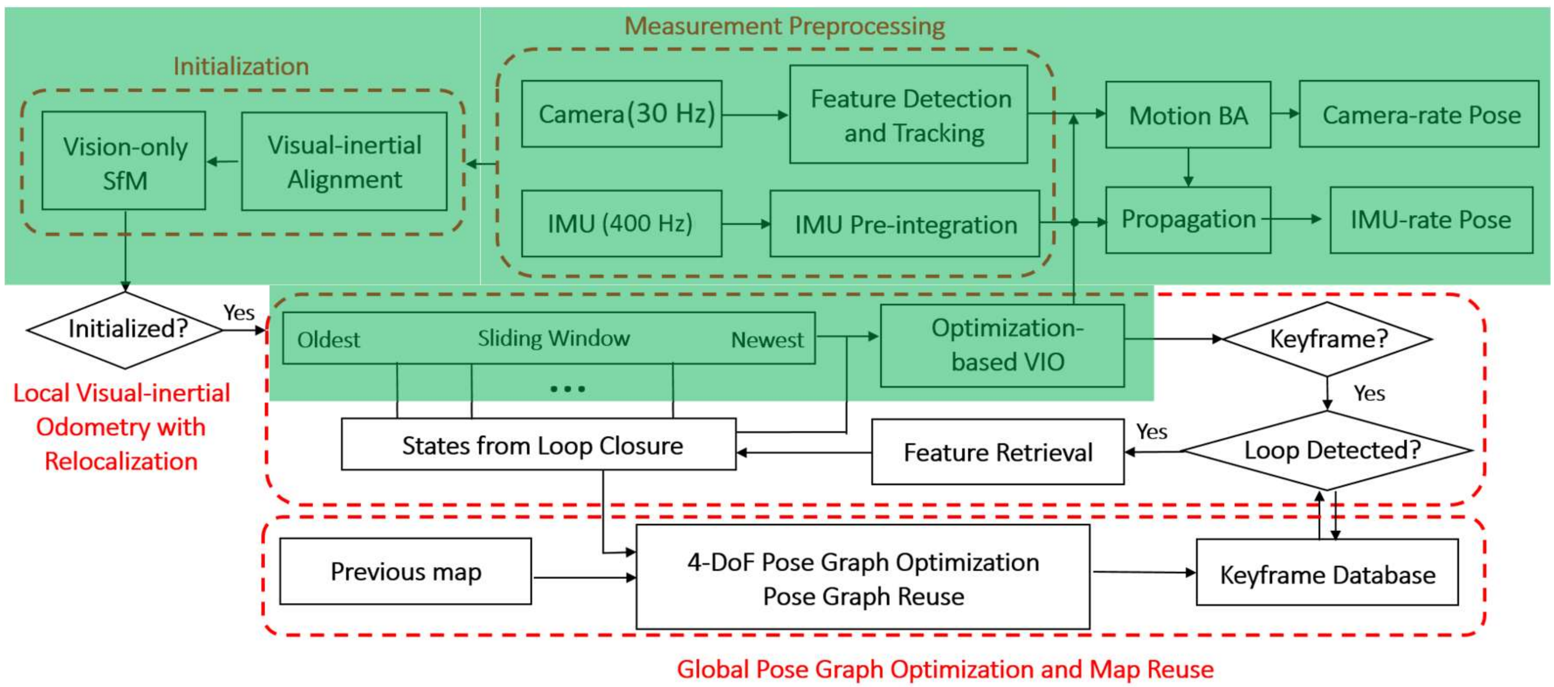
$$\mathcal{X}_I = [\mathbf{v}^{c_0}_{b_0}, \mathbf{v}^{c_0}_{b_1}, \cdots \mathbf{v}^{c_0}_{b_n}, \mathbf{g}^{c_0}, s]$$

$$\min_{\mathcal{X}_I} \sum_{k \in \mathcal{B}} \left\| \hat{\mathbf{z}}^{b_k}_{b_{k+1}} - \mathbf{H}^{b_k}_{b_{k+1}}\mathcal{X}_I \right\|^2$$



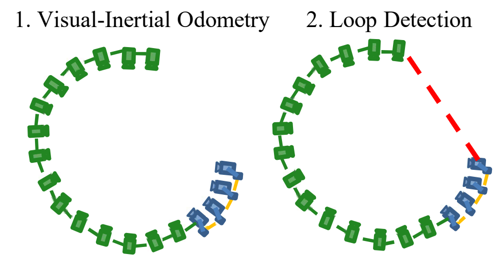
Monocular Visual-Inertial SLAM

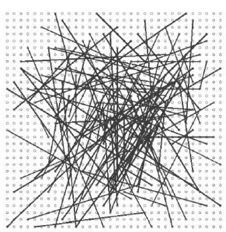
- System diagram

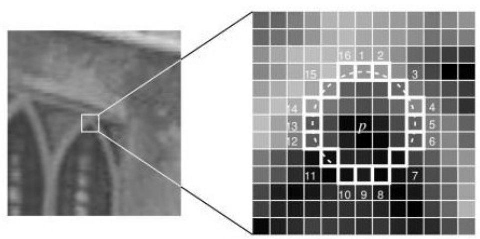


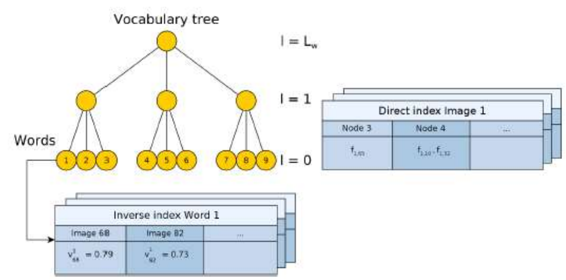
Loop Closure

- Loop detection
  - Describe features by BRIEF
    - Extract new FAST features (500, only use for loop detection)
  - Query Bag-of-Word (DBoW2)
    - Return loop candidates





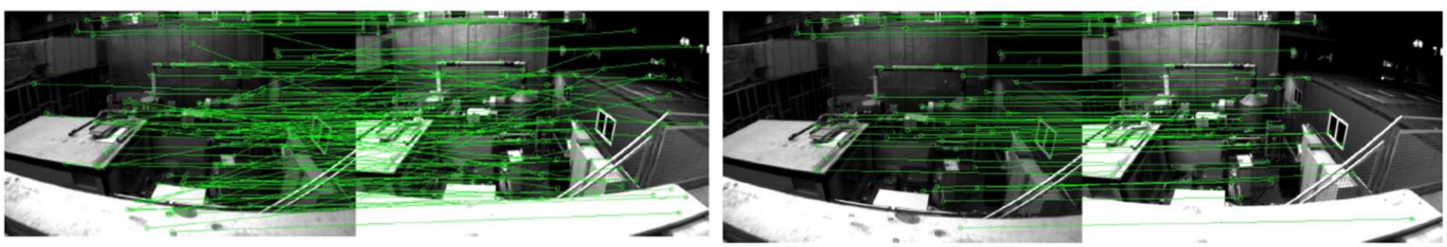




Calonder, Michael, et al. "Brief: Binary robust independent elementary features." *Computer Vision–ECCV 2010* (2010): 778-792.
Gálvez-López, Dorian, and Juan D. Tardos. "Bags of binary words for fast place recognition in image sequences." *IEEE Transactions on Robotics* 28.5 (2012): 1188-1197.

Loop Closure

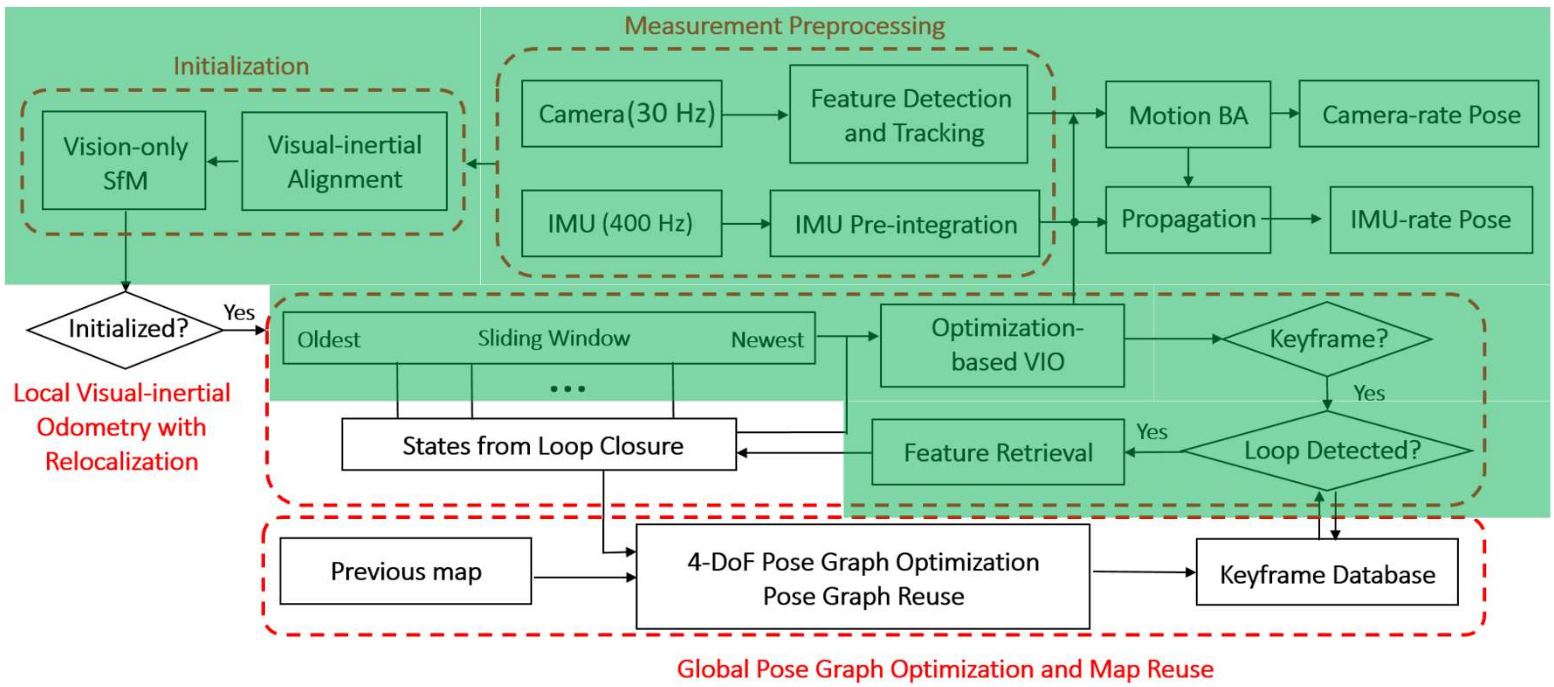
- Feature Retrieving
  - Try to retrieve matches for features that are used in the VIO
  - BRIEF descriptor match
  - Geometric check
    - Fundamental matrix test with RANSAC
    - At least 30 inliers
- Output:
  - Loop closure frames with known pose
  - Feature matches between VIO frames and loop closure frames



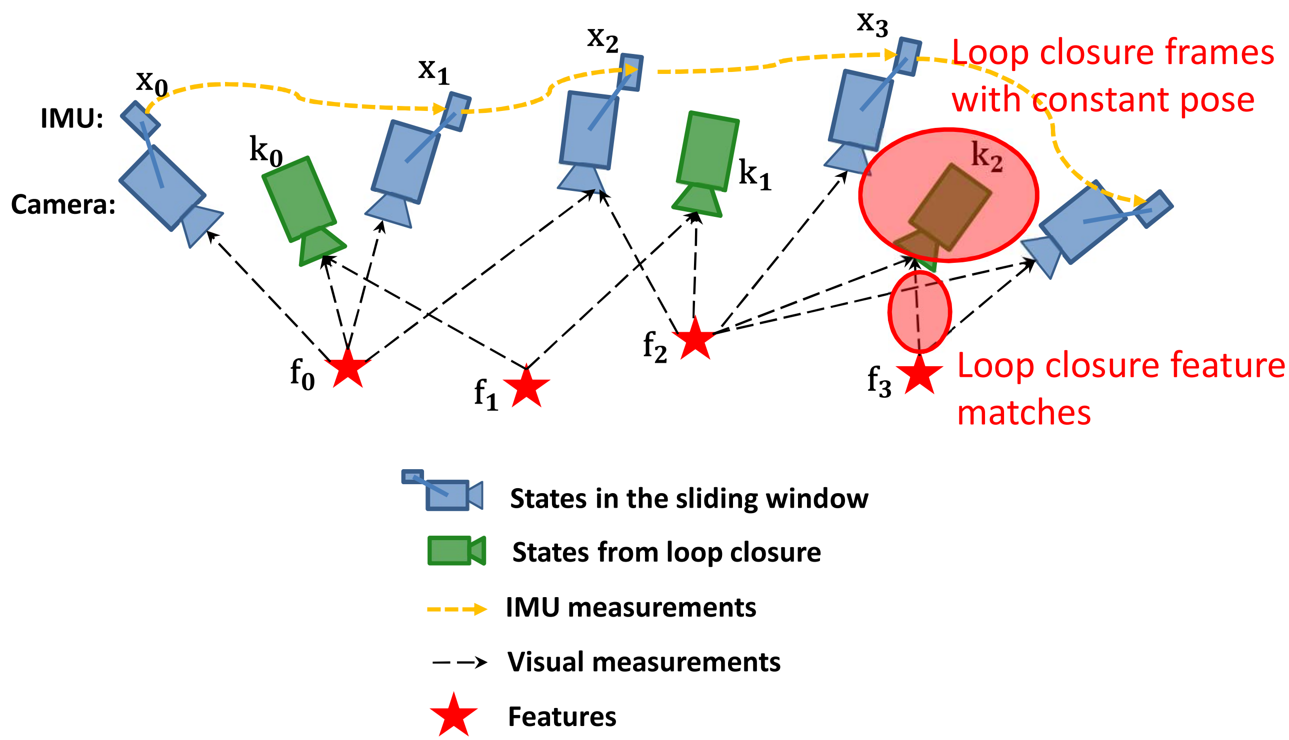
(a) (b)

Monocular Visual-Inertial SLAM

- System diagram

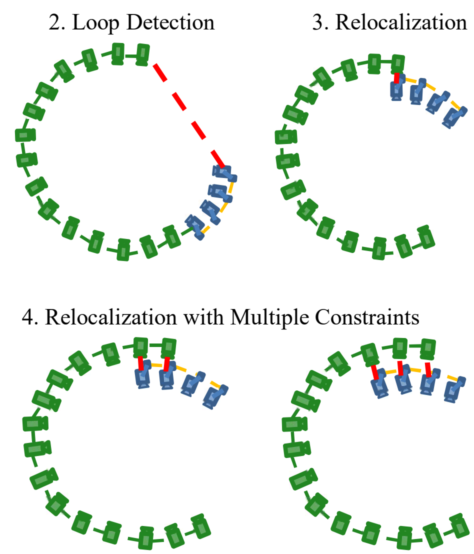


Monocular Visual-Inertial Odometry with Relozalization



Monocular Visual-Inertial Odometry with Relozalization

- Relocalization
  - Visual measurements for tightly-coupled relocalization
    - Observation of retrieved features in loop closure frames
    - Poses of loop closure frames are constant
    - No increase in state vector dimension for relocalization
    - Allows multi-constraint relocalization



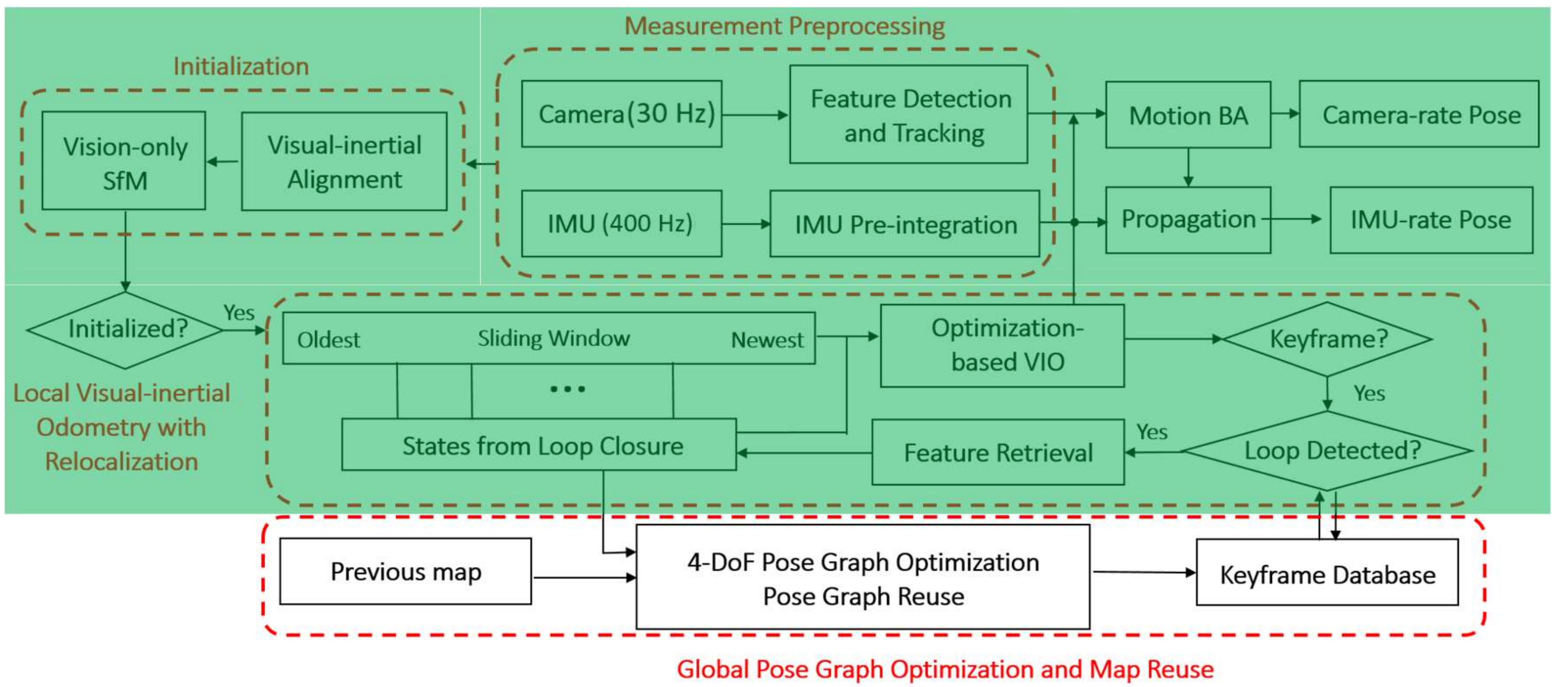
$$\min_{\mathcal{X}} \left\{ \|\mathbf{r}_p - \mathbf{H}_p\mathcal{X}\|^2 + \sum_{k\in\mathcal{B}} \left\|\mathbf{r}_\mathcal{B}(\hat{\mathbf{z}}^{b_k}_{b_{k+1}},\mathcal{X})\right\|^2_{\mathbf{P}^{b_k}_{b_{k+1}}} + \sum_{(l,j)\in\mathcal{C}} \left\|\mathbf{r}_\mathcal{C}(\hat{\mathbf{z}}^{c_j}_l,\mathcal{X})\right\|^2_{\mathbf{P}^{c_j}_l} + \sum_{(l,v)\in\mathcal{L}} \left\|\mathbf{r}_\mathcal{C}(\hat{\mathbf{z}}^{v}_l,\mathcal{X},\hat{\mathbf{q}}^w_v,\hat{\mathbf{p}}^w_v)\right\|^2_{\mathbf{P}^{c_v}_l} \right\}, \tag{22}$$

VIO residuals

Loop closure vision measurement residual

Monocular Visual-Inertial SLAM

- System diagram



Evaluation Results

Seq Name	APE(mm)	RPE(mm)	ARE(deg)	RRE(deg)	Badness	InitQuality
C0	67.812	25.907	3.529	0.635	7.697	3.475
C1	47.356	1.889	1.682	0.141	4.691	6.871
C2	69.143	14.785	2.049	0.321	5.879	3.711
C3	27.834	5.182	1.549	0.403	6.261	1.514
C4	66.927	21.137	0.878	0.123	1.494	7.033
C5	17.568	3.926	1.619	0.156	10.617	1.397
C6	49.625	10.866	1.743	0.284	1.922	5.526

Evaluation Results

Seq Name	APE(mm)	RPE(mm)	ARE(deg)	RRE(deg)	Badness	InitQuality
C7	14.735	2.676	0.805	0.130	9.699	1.848
C8	47.193	6.187	3.530	1.040	4.058	1.341
C9	20.167	3.180	1.619	0.318	15.422	2.264
C10	40.418	11.506	4.993	0.212	10.038	3.225
C11	31.688	6.602	1.726	0.589	9.659	1.498
D8	29.524	8.242	2.936	0.818	21.139	1.257
D9	14.064	1.484	1.896	0.180	0.218	0.910
D10	152.871	26.105	12.285	8.072	32.598	0.543

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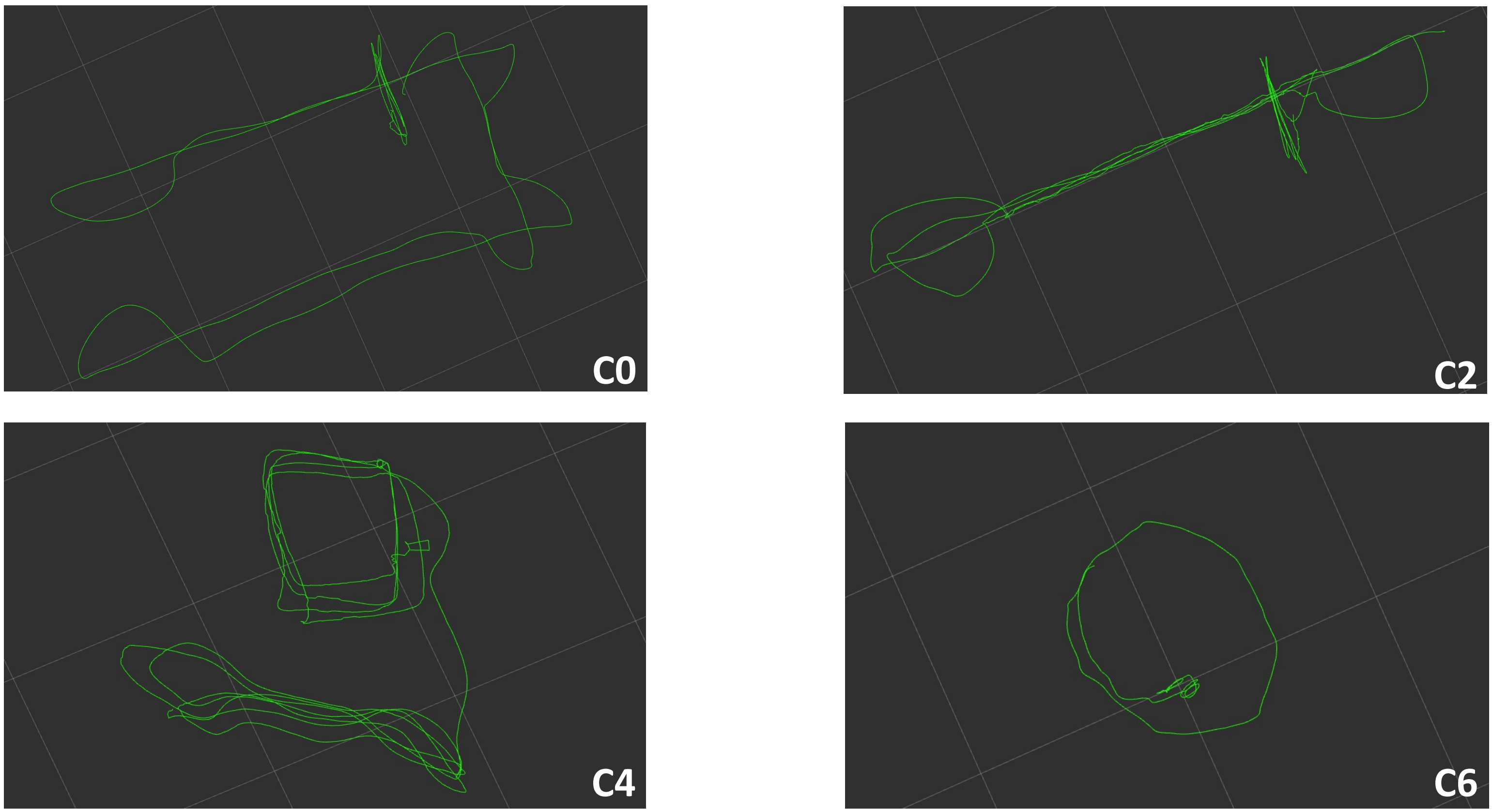
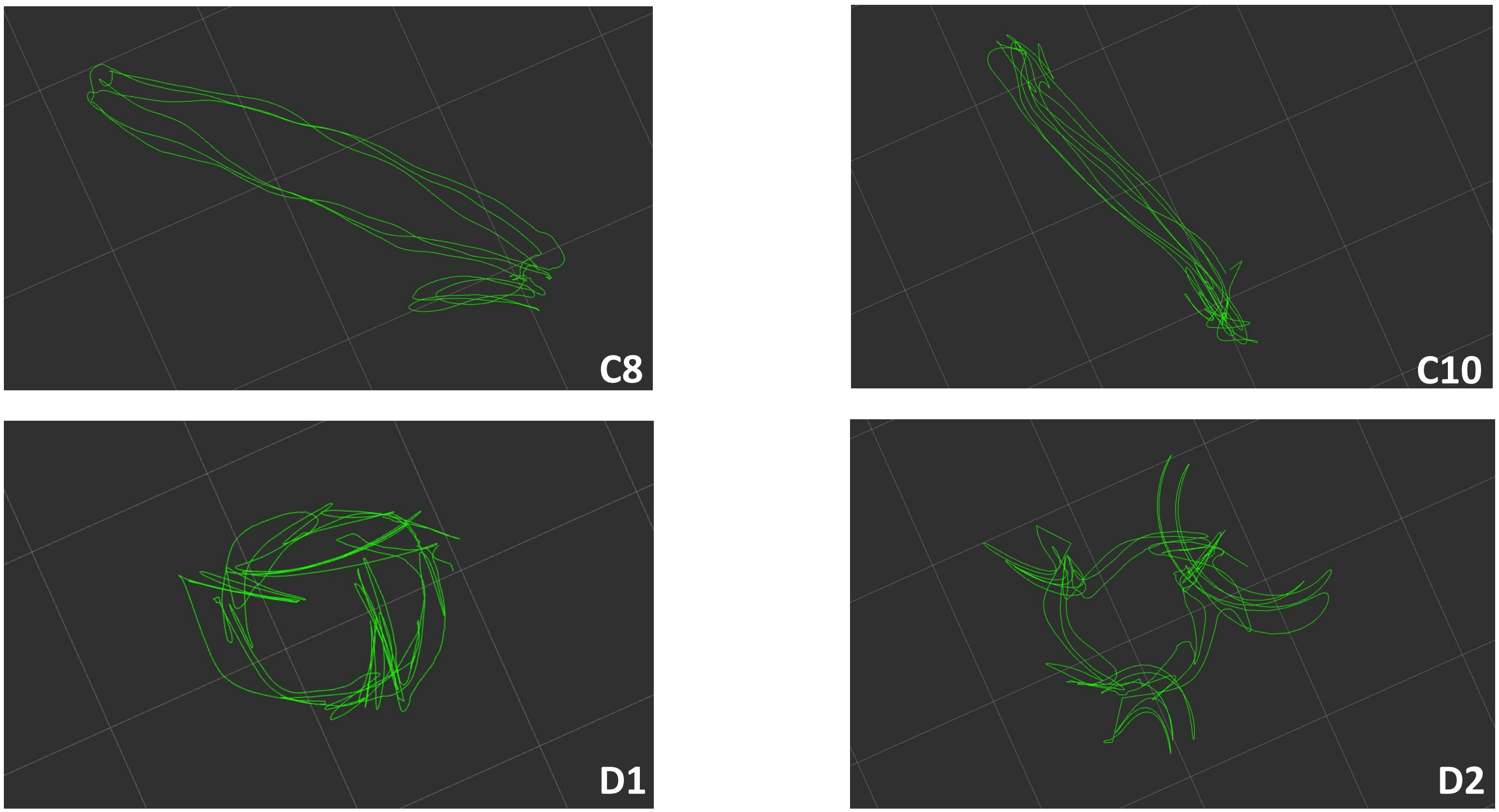
Evaluation Results



Evaluation Results



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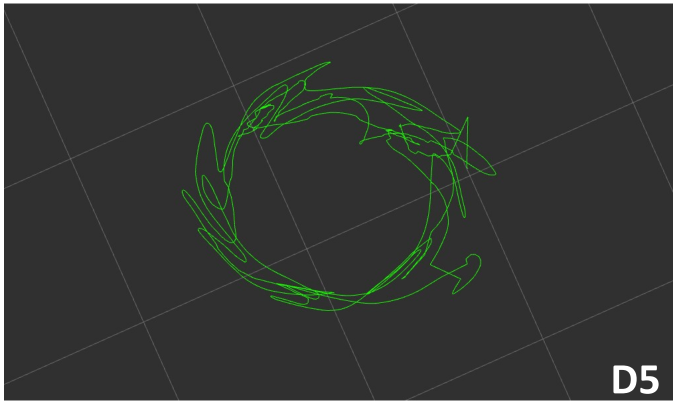
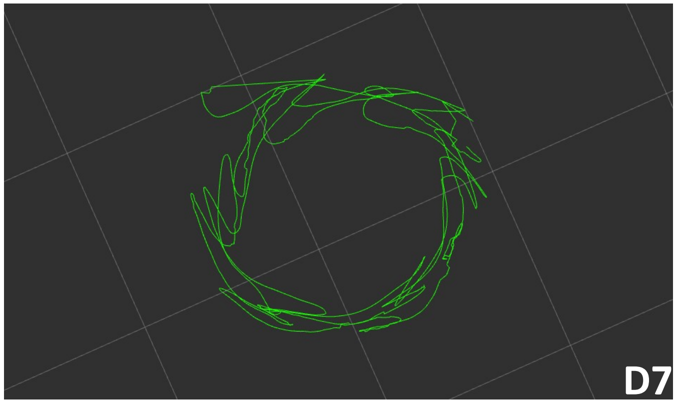
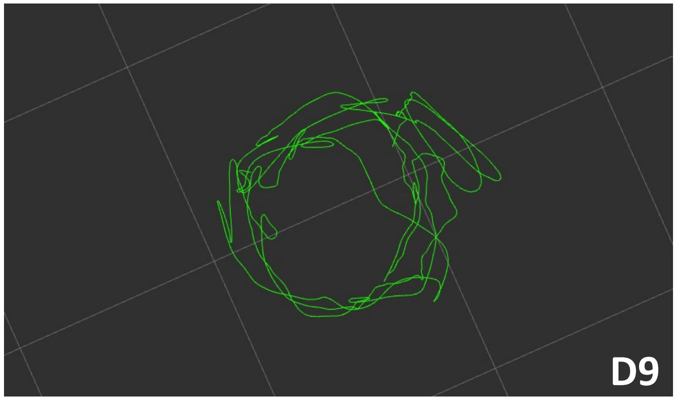
Evaluation Results







Thanks!

Questions?